AHRQ Grant Final Progress Report

Title of Project:
Discovery and Visualization of New Information from Clinical Reports in the EHR

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Structured Abstract

Purpose: Our long-term goal was to validate whether provider usage of clinical notes can be supported through refinement of automated methods to detect new information, facilitate new information visualization in practice, and optimize Electronic Health Record (EHR) clinical note user interface (UI) design. We sought to develop and validate an automated solution to detect new information in the EHR, consequently making clinicians more efficient, improve decision-making, decrease cognitive load, and potentially increase clinician satisfaction association with using clinical documents in EHR systems.
Scope: Increased interoperability of health data systems and EHRs result in rapidly growing volumes of electronic patient data, all of which are instantly made available through electronic interfaces, forcing fundamental changes in workflow, as well as increasing cognitive information processing demands on healthcare providers. We believe that the idea of highlighting new text will allow clinicians to focus on relevant information, yet provide a "lossless" means to access the entire original note.
Methods: We used a three-prong approach to classify new versus redundant clinical note information retrieval techniques: 1. Refined computational methods to identify new information; 2. Assess the effect of visualizing new information in a clinical inpatient setting; 3. Discover elements of a rationally designed EHR graphical UI to facilitate clinical document usage in practice.
Results: We were successfully able to develop computational models to identify new information, build a robust tool that identifies and captures new information in the clinical inpatient setting of the EHR, as well as conduct a series of usability studies around EHR use patterns with notes and EHR reading patterns by users. We successfully implemented this tool in a test Epic EHR environment at Fairview Health Services and performed pilot testing to determine the value of the tool for clinical patient care. We additionally did extensive usability testing on graphical UIs for ambulatory navigators, note organization for progress notes, and an unstructured clinical document query tool, as well as conducted ethnographic studies on note usage and creation by users within two different EHR systems..
Keywords: Health Information Exchange; Electronic Health Record; Decision Support Systems, Clinical; User Interface Optimization; Usability

Purpose (Objectives of the Study)

Our long-term goal was to validate whether provider usage of clinical notes can be supported through refinement of automated methods to detect new information, facilitation of new information visualization in practice, and Electronic Health Record (EHR) clinical note user interface (UI) optimization. EHR systems improve patient care by reducing redundancy in prescribing and computerized ordering but paradoxically also generate other types of information redundancy that lead to information overload. This presents a challenge for clinicians in providing safe and effective care especially with complex patient requiring synthesis of many clinical elements across a lengthy medical history.

While there is much interest in supporting evidence-based medicine, little attention has previously been given to assisting clinicians in navigating and synthesizing growing amounts of electronic data for individual patients. Unstructured narrative text is an important part of modern EHRs. While analyzing a collection of patient's notes can be formidable, it is necessary for making diagnostic and therapeutic decisions. This process can be hindered by a number of factors:

- Large amounts of redundant information carried over from one note to the next,
- An increasing number of clinical documents providing greater information access but also placing additional cognitive burden on clinicians,

- Cumbersome EHR UI design not optimized for clinical text, and
- Practical constraints of daily practice, particularly limited time for evaluating patients.

We sought to develop and validate an automated solution to detect new information in the EHR, consequently making clinicians more efficient, improve decision-making, decrease cognitive load, and potentially increase clinician satisfaction association with using clinical documents in EHR systems.

Our work was structured into three specific aims:

1. **Refine computational methods to identify new information in clinical notes.**
   We worked to advance existing methodologies and to identify new (and conversely redundant) information in clinical notes through the novel application of probabilistic language modeling enhanced with semantic similarity and relatedness measures
2. **Assess the effect of visualizing new information in clinical notes in an inpatient hospitalist setting.**
   Through our partnership with Fairview Health Services, we developed an innovative tool for visualizing new information and completed proof of concept testing with three Epic systems users of the new information note visualization tool. This was scaled back from our initial plan to complete a randomized trial with a group of hospitalists due to barriers in implementing our note visualization tool in the EHR with a change in the architecture of the newly upgraded system.
3. **Discover elements of a rationally designed EHR graphical UI to facilitate clinical document usage in practice.**
   We observed clinicians to understand key barriers in using clinical text and learned from current EHR vendor UIs (two separate EHRs and sites). User behavior was also tested with notes having different organizations to understand how this affects their experience with notes.

<u>Scope</u>

Background, Context, Incidence

With national mandates for universal adoption and "Meaningful Use" (1) of Electronic Health Record (*EHR*) systems, EHR systems are almost ubiquitous and viewed as vital for healthcare delivery. This is an unprecedented investment in health information technology (*HIT*) with primary motivations being expectations of improved patient safety, quality of care, and lower costs (2). EHR systems, however, represent both an opportunity and a challenge. Increased interoperability of HIT systems and EHRs result in rapidly growing volumes of electronic patient data, all of which are instantly made available through electronic interfaces, forcing fundamental changes in workflow, as well as increasing cognitive information processing demands on healthcare providers (3).

Information within modern EHR systems includes a mixture of highly structured data such as laboratory measurements, semi-structured templated data, and unstructured narrative or text. While structured data lends itself well to computation and aggregation, it can be difficult to interpret by clinicians due to loss of contextual information (4). Narrative often contains key clinical facts that can potentially be used for secondary care uses such as disease risk assessments when converted to a structured format. While there an important sets of efforts encouraging the collection of more structured data elements where possible for secondary functions and information reuse, the communication of nuanced and detailed patient information with clinical notes in both the inpatient and outpatient settings remains vital for care (5). When a clinician sees a new or complex patient requiring detailed review, the task of analyzing the patient's many electronic clinical documents is formidable. One of the major challenges with utilizing these notes is that clinical notes often contain large amounts of redundant information resulting in the situation where clinicians must mentally retrieve and mentally separate out the relevant new information from the rest of the note.

Introduction of HIT in any domain including healthcare transforms reasoning and alters workflow. Consistent with this is the recommendation from the informatics community that EHR systems should facilitate communication and information flow (6). While principles for visualization and interaction with structured EHR data elements are reported (7), little is known about the underlying cognitive processes used by healthcare providers daily in digesting and utilizing clinical notes. Despite section-based organization of clinical notes in most EHR systems, many clinicians believe that it is actually harder to find information of interest among many daily or episodic electronic clinical notes than in paper records.

For example, searching for an Infectious Disease consult note for an inpatient case after a 2-week hospital stay can be more difficult to find in an EHR system, whereas characteristic penmanship of the consultant could be readily identified in the paper chart (8). To use EHR systems effectively, clinicians must alter how they normally conceptualize and interact with the patient record (a.k.a., cognitive model) – a difficult and time-consuming process. Electronic clinical text in practice also often suffers greatly from "cutting-and-pasting" of redundant information and templated formats which automatically "pull in" information indiscriminately regardless of the significance of this information to the patient's condition (9). While this automation expedites documentation for billing and insurance purposes, the resulting redundancy of information may hurt downstream clinician consumers who must use these unfiltered notes to synthesize a patient's history and relevant pertinent positive and negative clinical elements all of which are used to formulate an appropriate diagnostic and/or therapeutic assessment and plan (5).

Cognitive load represents the cognitive resources utilized for learning, thinking, reasoning, and problem solving (10). All these activities rely on working memory that has limited information storage capacity and is prone to distractions and error resulting in poorer performance (11). A high cognitive load on working memory is influenced by the kind and amount of new information (extrinsic cognitive load) and the complexity of information (intrinsic cognitive load). A high cognitive load with computer systems can significantly interfere with user performance (12). In the clinical setting, additional contributing factors to this high cognitive load may include EHR system graphical UI designs not optimized for presenting information in clinical reports (6), high-stress, time- limited nature of clinical encounters (13, 14), and greater numbers of elderly patients with comorbidities requiring multidisciplinary care (also generating more clinical notes).

Information from clinical notes is central for patient summarization and clinical decision- making for providers caring for patients (15). While some have examined general decision- making processes with EHR systems in clinical workflow by providers (16) and others have qualitatively examined electronic note creation (17), processes surrounding consumption of clinical notes and their specific role in decision-making have not been well defined. In contrast to work in computational linguistics which focuses upon automated summarization of texts where information is extracted and separated from source the texts (15, 18-20), the idea of creating automated tools to visualize information *within* clinical notes "in situ" remains largely unexplored as does focused research into the optimal presentation of clinical notes in EHR system UI. We believe that the idea of highlighting new text with these techniques will offer significant advantages to summarization as they allow the clinicians to focus on relevant information, yet provide a "lossless" means to access the entire original note. Automated methods to classify text as new versus redundant could also potentially improve clinical note information retrieval techniques for research and other secondary uses of notes (21, 22).

Setting

Our study took place primarily at the University of Minnesota, with several sub-award institutions for associated work and expertise. The University of Minnesota is closely aligned with Fairview Health Services and houses their research-based data within the University of Minnesota Clinical Data Repository (CDR). The CDR is housed in a secure, PHI-compliant data environment. In addition, ethnographic experiments were held at Fairview Health Services and the Veteran's Administration Health System (in Minneapolis). Sub-award institutions included Fairview Health Services, Allina Health, and the University of Massachusetts Amherst.

Participants

Study participants were practicing clinicians who used the Epic EHR within the University of Minnesota Medical Center and the Veteran's Administration Health System.

Methods

Study Design

Our study aims center on improving the ability of clinicians to elucidate knowledge and to improve the use of clinical notes in practice for more effective patient care.

Specific Aim 1: Refine computational methods to identify new information in clinical notes

We developed automated methods for identifying clinically relevant new versus redundant information in EHR clinical notes through a statistical language model (n-grams model) modified with heuristic rules. This consisted of developing an expert-curated gold standard; developing and evaluating automatic methods; applying the best method to identify various types (i.e., new medication, new findings, new procedures) of clinically relevant new information in clinical notes; and quantifying and comparing redundancy across subject matter domain groups in the clinical setting.

Longitudinal electronic clinic notes were retrieved from the Fairview Health Services CDR at the University of Minnesota, and randomly selected 40 patients with multiple comorbidities, allowing for relatively large numbers of longitudinal records in the outpatient clinic setting. A corpus of 591 progress notes were arranged chronologically and manually reviewed by 4^{th} year medical students asked to use their clinical judgment to identify clinically relevant new information within each patient document, starting from the second document during an inpatient stay. The first note reviewed was typically the History & Physical Exam note, and used as a baseline for new information detection on the following notes. New information was identified and catalogued in the General Architecture for Text Engineering (GATE) software. GATE allows for the creation of a customized annotation schema for the annotation of text and XML outputs through a graphical user interface.

We used our previously developed clinical NLP system to process clinical text and to deal with key clinical text issues including lexical normalization (i.e., open source Lexical Variant Generation (LVG) (23) for medical words), and isolation of punctuation and other formatting (24). We developed n-gram models with and without semantic similarity algorithms, focusing on bigram models. We adapted various discounting algorithms (such as Laplace, Good-Turning, and Ney-Essen) to calculate the probability of bigrams. An optimal threshold probability value was used to identify new versus redundant information. In addition, we adapted semantic similarities algorithms to identify concepts who are semantically identical or close. Note redundancy between various specialties was evaluated on 71,021 outpatient notes and 64,695 inpatient notes from 500 solid organ transplant patients (April 2015 through August 2015).

Specific Aim 2: Assess the effect of visualizing new information in clinical notes in an inpatient hospitalist setting

The objective of this aim was to evaluate the efficacy of a visualization tool that will highlight new information in the inpatient setting with a formal prospective randomized trial with hospitalist clinicians. While originally intended to be a formal randomized trial, work on this aim was hindered by a number of factors. These include the development of a highly similar tool within the Epic EHR, difficulties in implementing our tool in the production zone of the Epic EHR at Fairview Health Services, and quality control issues with implementing our tool in the Epic EHR.

We performed two experiments examining how physicians read electronic progress notes, focusing on how section order impacts the experience of reading and reviewing notes. An EHR system prototype was populated with four deidentified patient cases that had nine progress notes per case. The notes were designed so that they could be presented to participants in the system with standard note sections presented in different orders. Participants were asked to review the notes for each case and provide a brief verbal summary. For each case, notes were presented to participants in section order. The four orders were: SOAP (subjective, objective, assessment, plan), APSO (assessment, plan subjective, objective), SAPO (subjective, assessment, plan, objective) and mix (three of each of the previous note types). After each case, participants completed the NASA-TLX instrument. After all four cases, participants completed a survey about their experience reading and reviewing notes and a brief interview.

In one experiment, 23 participants completed the experiment. We collected data about how long it took the participants to read each case, summarize each case, time spent scrolling and workload for each order. We also analyzed qualitative data about participants experience reading and review notes.

In the second experiment, 7 participants completed the experiment while wearing an eye tracking device. We coded the videos and analyzed data related to glace duration, number of glances, and time to first fixation for each section. We also analyzed the verbal summarizes to determine what section in the notes contained the information participants noted in the verbal summary to see if there was a relationship between time spent glancing at a section and including information from that section in the summary.

We were able to implement our tool into a test environment of the Epic EHR at Fairview Health Services and completed proof of concept testing with user participants. Pilot testing was comprised of having potential users view the tool and provide feedback (25).

We were able to leverage the technology infrastructure of this project to help develop an NLP system for clinical researchers, NLP-PIER (patient information extraction for research) (26, 27). See also Specific Aim 3.

Specific Aim 3: Discover elements of a rationally designed EHR graphical UI to facilitate clinical document usage in practice

We successfully leveraged two sets of providers at two sites with two EHRs for our first set of work. We conducted a series of ethnographic observations using 12 residents (2nd through 4th year) using the University of Minnesota Epic EHR and the Veterans Affairs Health Care System CPRS Vista EHR (28). Qualitative and quantitative clinical documentation process data was collected focusing on clinical note data entry and reading/retrieval tasks. Direct observation was used to collect data regarding user behaviors, their workflow and EHR usage centering on different uses and tasks associated with clinical documentation. Following data collection, Ethnographic Content Analysis was performed with integrated qualitative-quantitative research designs using NVivo Version 10.1.3 (29). High level themes were deduced through review and coded at a more granular level for note type, task performed, style adopted, and time to task.

We additionally performed several usability studies around task centered user interface design to develop clinical document UI. In one study, scenario based usability testing on two high fidelity simulated test patient charts in an Epic test environment replicating design and functionality of real work environments (30). We tested two user groups of physicians (n=14): attendings (n=8) and residents (n=6).

We performed usability testing to determine how physicians prefer to read progress notes and how clinicians access other clinical data information (31, 32). This included performing usability testing of two versions of an ambulatory navigator set to Meaningful Use requirements. We performed this testing at the University of Minnesota Academic Health Center with resident physicians in their 2nd to 4th years of training (n=8). Participants were asked to use think-aloud methods while performing tasks and data was analyzed for quantitative time to analyze the patient cases, perceived complexity of each case via the Single Ease Question, and usability of the navigator via the Systems Usability Score rating. Second, we analyzed the navigation pathways (clicks) that participants took through the navigators to locate assigned areas where they could complete tasks. Third, sessions were recorded and reviewed and coded for themes.

Our work on how providers access and search for clinical data information happened through usability testing of an unstructured clinical document query tool for researchers, called Natural Language Processing – Patient Information Extraction for Researchers (NLP-PIER) (33-35). NLP-PIER consists of full text search and structured Lucene queries that are build on United Medical Language System (UMLS) Concept Unique Identifiers (CUIs) (36). NLP-PIER is housed within the UMN Academic Health Center - Information Exchange in a secure PHI compliant environment. A convenience sample of eleven clinical research faculty participated in the study. screen capture software was used to record sessions (37). Participants were logged into NLP-PIER and were given a tour of the interface. Each participant was given an opportunity to ask questions. Participants were also provided with a “tip sheet” of helpful hints. This was done to partially mimic “real-world” setting, where participants would have time to test out the interface and ask questions of colleagues. The first part of the usability assessment consisted of each participant completing two sets of tasks in the full text search interface. Following completion of tasks, participants completed the SUS (38) and raw NASA-TLX (39) surveys. Part two of the assessment was completed in the concept search interface. Similarly, participants completed two different sets of tasks using this interface. Participants then completed the SUS and NASA-TLX surveys as well as a demographic survey and a brief interview. To analyze participant opinions and feedback, we conducted interviews with participants.

Data Sources/Collection

Fairview Health Services is an integrated healthcare network with a number of direct affiliations with the University of Minnesota (UMN). Fairview is a large not-for-profit health care system in Minnesota with 12 hospitals and over 56 outpatient clinics. Fairview has been using Epic as its EHR system in its hospitals and clinics for over 5 years. Fairview maintains an electronic clinical data warehouse that is shared with the University of Minnesota for research purposes. We utilized progress notes, admission and discharge notes, and consultation notes in the inpatient and outpatient setting to develop methodologies to identify new information within subsequent progress notes for inpatient stays within the Fairview Health System.

Limitations

There are several limitations to our approach and this research. First, accurately identifying redundant information in clinical documentation using a hybrid of rule-based techniques and machine learning approaches poses a number of limitations on performance rates. Most profoundly, it is difficult to create an accurate gold standard upon which clinicians agree, and to discern accuracy at the corpus level. Additionally, during the development of our tool, Epic Systems implemented a similar copy/paste functionality tool directly in the EHR. This provided challenges in proving differences between the functionality of our tool versus Epic's iteration. There were further challenges in creating infrastructure to support the live implementation of our tool within the production zone of the Epic EHR at Fairview Health Services. Subsequently, Aim #2 had substantial delays and it was not possible to run a prospective randomized clinical trial. Our findings do provide insights and lessons learned to inform best practices for building UIs and implementing EHR-based tools in future.

<u>Results</u>

Principal Findings

We were successfully able to build a robust tool that identifies and captures new information in the clinical inpatient setting of the EHR. We successfully implemented this tool and tested it in the Epic EHR at Fairview Health Services and performed pilot testing to determine the value of the tool for clinical patient care. We additionally did extensive usability testing on graphical UIs for ambulatory navigators, note organization with progress notes, and an unstructured clinical document query tool. The grant also supported the development of an NLP tool for researchers and studies around literature-based discovery.

Outcomes

While we encountered a number of challenges in implementing our tool into real-time production Epic EHR, we feel this work drives the discipline forward in identifying metrics to decrease clinical care burden on physicians and is echoed in the efforts of Epic Systems to create a highly similar tool to be implemented in their EHR system.

Specific Aim 1: Refine computational methods to identify new information in clinical notes

In support of specific aim 1, we have built a development platform and deployed this platform in research environments of the Fairview Epic EHR with the assistance of Epic Corporation. Following the integration within BioMedICUS of all rich text format (RTF) notes, we have integrated all historic RTF clinical notes (over 90M) into the overall platform. This platform has been expanded to include procedures, signs and symptoms, and medication visualization. These methods have been formally evaluated.

We developed automated methods to identify redundancy in clinical inpatient and outpatient records from the Fairview Health Services Epic EHR (40, 41) through a three-part methodological approach consisting of: developing a reference standard of new information with associated information type; identification of new information using an *n*-gram modeling technique for modified clinical texts; and extraction of semantic types and key terms from identified new information. Automated methods were then compared to the manually created reference standard. Our best method achieved at best performance of 0.87 recall, 0.62 precision, and 0.72 F-measure. Addition of semantic similarity metrics compared to baseline improved recall but otherwise resulted in similar performance.

In inpatient notes, sections with the most clinically relevant new information were Physical Exam (33%), Assessment & Plan (27%), and Medication (14%) (42). In outpatient notes, sections with most clinically relevant new information were Problem (34%), Medication (32%), and Laboratory Results (17%) (43). Finally, our work “Detecting Clinically Relevant New Information in Clinical Notes Across Specialties and Settings” published in *BMC Medical Informatics and Decision Making* (44) worked to quantify redundancy using automated methods between clinical specialties found overall redundancy rates of 64.3% in clinical notes by various subject matter domains including Emergency Medicine, Critical Care Medicine, Surgery, Pediatrics, and other specialties represented in 71,021 outpatient notes and 64,695 inpatient notes. A comparison was done to determine rates of irrelevant information in inpatient versus outpatient clinical notes. While outpatient and inpatient notes had relatively similar levels of high redundancy (61% and 68% respectively), redundancy differed by author specialty with mean redundancy of 75%, 66%, 57%, and 55% observed in pediatric, internal medicine, psychiatry, and surgical notes, respectively. This comparison revealed similar rates of redundancy between clinical settings (76%) (42).

In addition to visualizing new information in text, we expanded our methods beyond clinical documents to develop methods to visualize drug-drug and drug-supplement interactions. This work was expanded to evaluate associations between drug-drug interactions and drug-supplement interactions present in biomedical literature and the clinical EHR (45-47). Related semantic predication and machine-learning methods were used to extract potential interaction pathways and were evaluated by expert review. Our literature-based discovery demonstrated the value of leveraging automated methods to yield both known and unknown drug-supplement interactions, with a specific focus on the CYP450 gene family (45). This work was expanded to identify drug-supplement interactions in the EHR, identifying that approximately 40% of listed medications were related to supplements for our dataset, and that over 60% of related supplement terms cannot be mapped to UMLS CUIs (46). This demonstrates a need for better documentation representation of potentially dangerous drug-supplement interactions. When identifying drug-drug interactions in outpatient notes, we found 14 unknown pairs of interacting drugs in the medication list of clinical data after physician selection of interesting predications, in addition to a number of known drug-drug interactions (47).

This work was further expanded to detect infusion-related reaction (IRR) and specifically to visualize their occurrences associated with the drug treatment for breast cancer patients (48). Similar to new information, this visualization would potentially assist clinicians to improve patient safety and help researchers model IRRs and analyze their risk factors. We developed and evaluated a phenotyping algorithm to detect IRRs for breast cancer patients. We also designed a visualization prototype to render IRR patients’ medications, lab tests, and vital signs over time. By comparing with the 42 randomly selected doses that are manually labeled by a domain expert, the sensitivity, positive predictive value, specificity, and negative predictive value of the algorithms are 69% , 60%, 79%, and 85%, respectively. Using the algorithm, an incidence of 6.4% of patients and 1.8% of doses for docetaxel, 8.7% and 3.2% of doxurubicin, 10.4% and 1.2% for paclitaxel, 16.1% and 1.1% for trastuzumab were identified retrospectively. The incidences estimated are consistent with related studies. In addition, we proposed three phenotyping algorithms to assess breast cancer patients’ susceptibility to cardiotoxicity caused by five first-line antineoplastic drugs: (1) casual phenotype model to predict the patients’ risk of cardiotoxicity as the difference between heart disease risks with exposure and non-exposure to the drugs; (2) regular predictive model; (3) combined predictive model of the above two models (49). Concordances for the three methods were 0.60, 0.62, and 0.68. When considering all exposed patients, concordances were 0.66, 0.58, and 0.65 at 280 days after treatment. The study demonstrates the potential utility of causal phenotyping.

Specific Aim 2: Assess the effect of visualizing new information in clinical notes in an inpatient hospitalist setting

Our studies on note section ordering revealed several insights into how physicians review clinical notes (50, 51). Our initial study on time to read and review notes demonstrated differences in reading time between section orders with the mixed order taking the longest time for physicians to review (50). Qualitatively, participants reported frustrations with auto populated data and with notes being inconsistent. In the eye tracking study (52), we identified wide variability in the way in which participants read notes, with the strongest variability occurring with the mixed order. Our study indicates that participants read notes in a fragmented way. There was no relationship between time spent reading a section and including information from that section in the verbal summary.

While we were unable to implement a full-scale prospective randomized clinical trial to test our system, we made significant headway in understanding institutional requirements for building HIT infrastructure that supports real-time clinical decision support within the EHR. The collaboration between UMN, Fairview, and Epic made it possible to deploy our tool in research environments in order to do pilot testing that will be presented in March 2019 at the American Medical Informatics Association Informatics Summits. Significant planning was completed as well as piloting functionality to select end-user physicians. In preparation for formal evaluation, we completed a usability study of a clinical researcher interface with EHR notes as well as a controlled study of note reading patterns when progress notes are arranged with different types organization

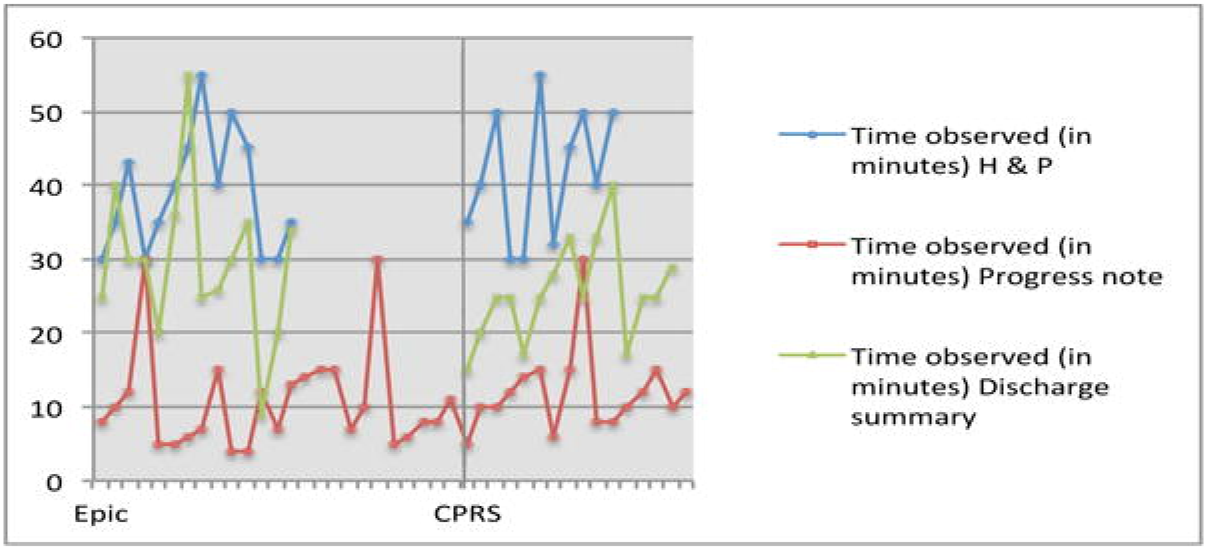
We also assessed system usability for an ambulatory navigator to test our approach and instruments with a different set of EHR system functionality (33-35) (see Specific Aim 3). When assessing system usability of the NLP-PIER clinical document search engine, clinician researchers stated that this tool would be useful for their research (33). NLP-PIER is equipped with a full-text search interface and UMLS CUI interface (53). SUS scores were 69.4 and 66.1 respectively, with NASA-TLX scores of 18.8 and 21.8 respectively (33). These scores indicate marginal usability. We have since incorporated feedback from this study into design for the next release of NLP-PIER.

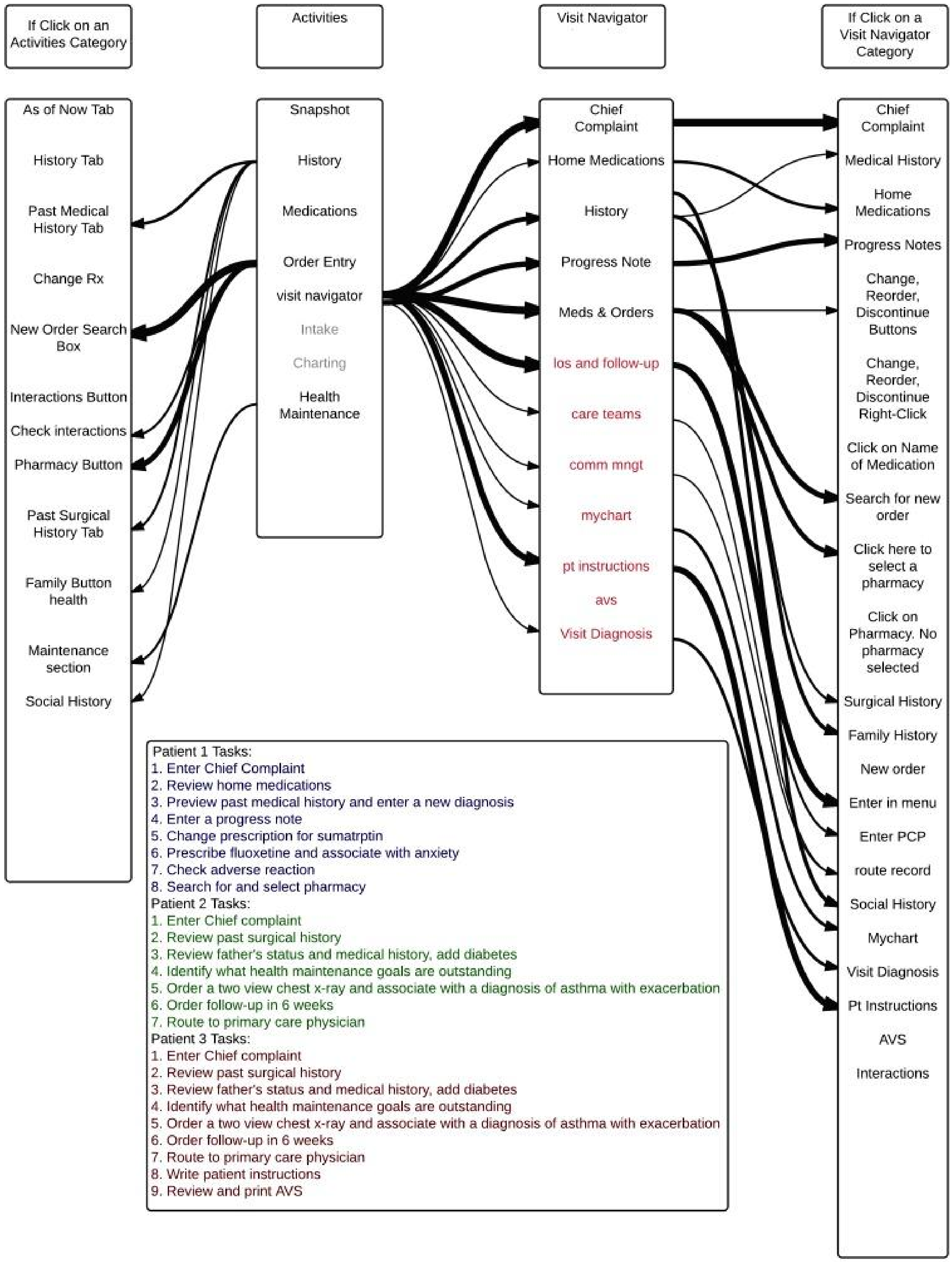
Specific Aim 3: Discover elements of a rationally designed EHR graphical UI to facilitate clinical document usage in practice

In our ethnographic experiments, we found lower satisfaction rates with EHR usage correlated with increasing clinical experience in years based on the Systems Usability Scoring system (28). Our study examined residents and attendings in a naturalistic setting that demonstrated several key patterns of EHR usage with note reading and note creation. For note entry, we examined five templates for History and Physical Exam notes, six templates for progress notes, and five templates for discharge summaries. Users typically prefer a single note writing style and do not deviate from their preferred template.

We found that note reading pattern relied heavily on stimulus initiating the task. We characterized seven reading patterns for History and Physical Exam notes, seven reading patterns for progress notes, and two reading patterns for discharge summaries (30). Note reading patterns were not always indicative of note writing patterns, and demonstrate that providers have different workflows and needs when reading a note as opposed to writing a note. This demonstrates need to uncouple note order display in the EHR from note writing order.

In the bake-off between the Epic EHR and CPRS Vista EHR (28), we found similar amounts of time were spent doing note entry for each note type, with History and Physical Exam notes taking the most time (mean 39 and 42 minutes, respectively), and progress notes taking the least time (mean 11 and 12 minutes, respectively) (28).

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Past Medical History Tab
Change Rx
New Order Search Box
Interactions Button
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Pharmacy Button
Past Surgical History Tab
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Medications
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Intake
Charting
Health Maintenance
Chief Complaint
Home Medications
History
Progress Note
Meds & Orders
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care teams
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mychart
pt instructions
avs
Visit Diagnosis
Chief Complaint
Medical History
Home Medications
Progress Notes
Change, Reorder, Discontinue Buttons
Change, Reorder, Discontinue Right-Click
Click on Name of Medication
Search for new order
Click here to select a pharmacy
Click on Pharmacy. No pharmacy selected
Surgical History
Family History
New order
Enter in menu
Enter PCP
route record
Social History
Mychart
Visit Diagnosis
Pt Instructions
AVS
Interactions
Patient 1 Tasks:
1. Enter Chief Complaint
2. Review home medications
3. Preview past medical history and enter a new diagnosis
4. Enter a progress note
5. Change prescription for sumatrptin
6. Prescribe fluoxetine and associate with anxiety
7. Check adverse reaction
8. Search for and select pharmacy
Patient 2 Tasks:
1. Enter Chief complaint
2. Review past surgical history
3. Review father's status and medical history, add diabetes
4. Identify what health maintenance goals are outstanding
5. Order a two view chest x-ray and associate with a diagnosis of asthma with exacerbation
6. Order follow-up in 6 weeks
7. Route to primary care physician
Patient 3 Tasks:
1. Enter Chief complaint
2. Review past surgical history
3. Review father's status and medical history, add diabetes
4. Identify what health maintenance goals are outstanding
5. Order a two view chest x-ray and associate with a diagnosis of asthma with exacerbation
6. Order follow-up in 6 weeks
7. Route to primary care physician
8. Write patient instructions
9. Review and print AVS

Our study testing two versions of an ambulatory navigator resulted in mixed preferences in navigators based on SUS scores (31, 32). Several users also took longer to complete the assigned tasks in the new navigator compared with the old navigator. There was a slight preference for the new navigator, although this was not statistically significant (32). We analyzed navigator pathways for the original navigator to provide a better understanding how numerous pathways are used for accomplishing many tasks. Between two and five pathways were used for each task, and for certain tasks other pathways were available but not used by participants. Regardless of which navigator was used, there was little standardization observed in navigation pathways between participants. We additionally identified several links and buttons available in the original navigator that were not utilized by participants (40 available; 11 used) (32).

List of Publications and Products

1. Arsoniadis EG, Khatri R, Marquard J, Moors C, Kim M, Melton, GB. A Review and Analysis of Rounding and Handoff Document Content in Inpatient Resident Physician Teams. Proceedings of the American Medical Informatics Annual Symposium. November 14-18, 2015. San Francisco, CA.
2. Bill R, Melton GB, Gottschalk B, Ring A, Dale JL, Vinals J, Lamblin AF, Pakhomov S. Enabling Use of High Performance Computing for Secure Processing of Protected Health Information. AMIA Jt Summits Transl Sci Proc. March 23-27, 2015. San Francisco, CA.
3. Fan Y, He L, Pakhomov SVS, Melton GB, Zhang R. Classifying Supplement Use Status in Clinical Notes. AMIA Jt Summits Transl Sci Proc. 2017 Jul 26;2017:493-501. eCollection 2017. PubMed PMID: 28815149; PubMed Central PMCID: PMC5543386.
4. Hultman G, Arsoniadis E, Marquard J, Rizvi R, Khairat S, Fickau K, Melton GB. Usability Testing of an Ambulatory Navigator. Proceedings of the American Medical Informatics Annual Symposium. November 14-18, 2015. San Francisco, CA.
5. Hultman G, Marquard J, Arsoniadis E, Mink PJ, Rizvi R, Ramer T, Khairat S, Fickau K, Melton GB. Usability Testing of Two Ambulatory EHR Navigators. Applied Clinical Informatics. 2016 Jun 15;7(2):502-15. doi: 10.4338/ACI-2015-10-RA-0129. eCollection 2016. PMID: 27437057 PMCID: PMC4941856.
6. Hultman G, Marquard J, Kandaswamy S, Lindemann EA, Melton GB. How do physicians read electronic progress notes? Proceedings of the American Medical Informatics Association Symposium. November 4-8, 2017. Washington, DC.
7. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of an Unstructured Clinical Document Query Tool for Researchers. Proceedings of the American Medical Informatics Association Informatics Summit Symposium. 2018:84-93.
8. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of NLP-PIER: A Clinical Document Search Engine for Researchers. Stud Health Technol Inform. 2017;245:1269. PubMed PMID: 29295354; PubMed Central PMCID: PMC6188640.
9. Hultman G, McEwan R, Pakhomov S, Skube S, Melton GB. Usability Testing of a Clinical Document Search Engine for Researchers. AMIA Jt Summits Transl Sci Proc. March 27-30, 2017. San Francisco, CA.
10. Hultman G, Zhang R, Knoll B, McEwan R, Skube S, Melton GB. Visualization of Clinically Relevant New Information from Clinical Reports in the EHR. AMIA Jt Summits Transl Sci Proc. 2018. *(In Press).*

11. Hultman GM, Marquard J, Ighile O, Farri O, Lindemann E, Arsoniadis EG, Pakhomov SVS, Melton GB. Does Section Order Affect Physicians' Experiences Reviewing Ambulatory Progress Notes? Proceedings of the American Medical Informatics Annual Symposium. November 12-16, 2016. Chicago, IL.
12. Hultman GM, Marquard J, Swaminathan K, Lindemann EA, Pakhomov S, Melton GB. Electronic Progress Note Reading Patterns: An Eye Tracking Analysis. Stud Health Technol Inform. 2019. *(Submitted).*
13. Hultman GM, Marquard JL, Lindemann E, Arsoniadis E, Pakhomov S, Melton GB. Physician Experience with Electronic Progress Notes: A Mixed-Methods Evaluation. Applied Clinical Informatics. *(Submitted).*
14. Knoll BC, Lindemann EA, Albert AL, Melton GB, Pakhomov SVS. Recurrent Deep Network Models for Clinical NLP Tasks: Use Case with Sentence Boundary Disambiguation. Stud Health Technol Inform. 2018. *(Submitted).*
15. Manohar N, Adam TJ, Pakhomov SV, Melton GB, Zhang R. Evaluation of Herbal and Dietary Supplement Resource Term Coverage. Stud Health Technol Inform. 2015;216:785-9. PubMed PMID: 26262159; PubMed Central PMCID: PMC4801024.
16. McEwan R, Melton GB, Knoll BC, Wang Y, Hultman G, Dale JL, Meyer T, Pakhomov SV. NLP-PIER: A Scalable Natural Language Processing, Indexing, and Searching Architecture for Clinical Notes. AMIA Jt Summits Transl Sci Proc. 2016 Jul 20;2016:150-9. eCollection 2016. PubMed PMID: 27570663; PubMed Central PMCID: PMC5001745.
17. Melton GB, Wang Y, Arsoniadis E, Pakhomov SV, Adam TJ, Kwaan MR, Rothenberger DA, Chen ES. Analyzing Operative Note Structure in Development of a Section Header Resource. Stud Health Technol Inform. 2015;216:821-6. PubMed PMID: 26262166; PubMed Central PMCID: PMC4781788.
18. Melton GB, Wang Y, Arsoniadis E, et al. Analyzing Operative Note Structure in Development of a Section Header Resource. Stud Health Technol Inform. 2015;216:821-6.
19. Rajamani S, Chen ES, Akre ME, Wang Y, Melton GB. Assessing the adequacy of the HL7/LOINC Document Ontology Role axis. J Am Med Inform Assoc. 2015 May;22(3):615-20. doi: 10.1136/amiajnl-2014-003100. Epub 2014 Oct 28. PubMed PMID: 25352569; PubMed Central PMCID: PMC5901117.
20. Rajamani S, Chen ES, Wang Y, Melton GB. Extending the HL7/LOINC Document Ontology Settings of Care. AMIA Annu Symp Proc. 2014 Nov 14;2014:994-1001. eCollection 2014. PubMed PMID: 25954408; PubMed Central PMCID: PMC4419877.
21. Rizvi RF, Adam TJ, Lindemann EA, Vasilakes J, Pakhomov SV, Bishop JR, Melton GB, Zhang R. Comparing Existing Resources to Represent Dietary Supplements. AMIA Jt Summits Transl Sci Proc. 2018 May 18;2017:207-216. eCollection 2018. PubMed PMID: 29888074; PubMed Central PMCID: PMC5961776.
22. Rizvi RF, Harder KA, Hultman GM, Adam TJ, Kim M, Pakhomov SV, Melton GB. A comparative observational study of inpatient clinical note-entry and reading/retrieval styles adopted by physicians. Int J Med Inform. 2016 Jun;90:1-11. doi: 10.1016/j.ijmedinf.2016.02.011. Epub 2016 Mar 2. PubMed PMID: 27103191; PubMed Central PMCID: PMC5534410.
23. Rizvi RF, Marquard JL, Seywerd MA, Adam TJ, Elison JT, Hultman GM, Harder KA, Melton GB. Usability Evaluation of an EHR's Clinical Notes Interface from Attendings and Residents Perspectives-An Exploratory Study. Studies in Health Technology and Informatics (MedInfo 2017). 2017;245:1128-1132. PMID: 29295278.
24. Rizvi R, Seywerd M, Arsoniadis EG, Adam TJ, Melton-Meaux GB. Leveraging a Proprietary Electronic Health Record System to Create High-Fidelity, Smart Test Patients. iHealth 2016 Clinical Informatics Conference. May 2-4, 2016. Philadelphia, PA.

25. Silverman G, Lindemann EA, Rajamani G, Finzel RF, McEwan R, Knoll BC, Pakhomov SVS, Melton GB, Tignanelli CJ. Named Entity Phrase Extraction in Trauma Surgery. Stud Health Technol Inform. 2018. *(Submitted)*.
26. Sun D, Sarda G, Skube SJ, Blaes AH, Khairat S, Melton GB, Zhang R. Phenotyping and Visualizing Infusion-Related Reactions for Breast Cancer Patients. Stud Health Technol Inform. 2017;245:599-603. PubMed PMID: 29295166; PubMed Central PMCID: PMC5760174.
27. Sun D, Simon GJ, Skube S, Blaes AH, Melton GB, Zhang R. Causal Phenotyping for Susceptibility to Cardiotoxicity from Antineoplastic Breast Cancer Medications. AMIA Annu Symp Proc. 2018 Apr 16;2017:1655-1664. eCollection 2017. PubMed PMID: 29854236; PubMed Central PMCID: PMC5977581.
28. Wang Y, Chen ES, Leppik I, Pakhomov S, Sarkar IN, Melton GB. Identifying Family History and Substance Use Associations for Adult Epilepsy from the Electronic Health Record. AMIA Jt Summits Transl Sci Proc. 2016 Jul 20;2016:250-9. eCollection 2016. PubMed PMID: 27570679; PubMed Central PMCID: PMC5001738.
29. Wang Y, Pakhomov S, Dale JL, Chen ES, Melton GB. Application of HL7/LOINC Document Ontology to a University-Affiliated Integrated Health System Research Clinical Data Repository. AMIA Jt Summits Transl Sci Proc. 2014 Apr 7;2014:230-4. eCollection 2014. PubMed PMID: 25954591; PubMed Central PMCID: PMC4419769.
30. Zhang R, Adam TJ, Simon G, Cairelli MJ, Rindflesch T, Pakhomov S, Melton GB. Mining Biomedical Literature to Explore Interactions between Cancer Drugs and Dietary Supplements. AMIA Jt Summits Transl Sci Proc. 2015 Mar 23;2015:69-73. eCollection 2015. PubMed PMID: 26306241; PubMed Central PMCID: PMC4525230.
31. Zhang R, Cairelli MJ, Fiszman M, Kilicoglu H, Rindflesch TC, Pakhomov SV, Melton GB. Exploiting Literature-derived Knowledge and Semantics to Identify Potential Prostate Cancer Drugs. Cancer Inform. 2014 Oct 14;13(Suppl 1):103-11. doi: 10.4137/CIN.S13889. eCollection 2014. PubMed PMID: 25392688; PubMed Central PMCID: PMC4216049.
32. Zhang R, Cairelli MJ, Fiszman M, Rosemblat G, Kilicoglu H, Rindflesch TC, Pakhomov SV, Melton GB. Using semantic predications to uncover drug-drug interactions in clinical data. J Biomed Inform. 2014 Jun;49:134-47. doi: 10.1016/j.jbi.2014.01.004. Epub 2014 Jan 19. PubMed PMID: 24448204; PubMed Central PMCID: PMC4058371.
33. Zhang R, Manohar N, Arsoniadis E, Wang Y, Adam TJ, Pakhomov SV, Melton GB. Evaluating Term Coverage of Herbal and Dietary Supplements in Electronic Health Records. AMIA Annu Symp Proc. 2015 Nov 5;2015:1361-70. eCollection 2015. PubMed PMID: 26958277; PubMed Central PMCID: PMC4765597.
34. Zhang R, Pakhomov SV, Lee JT, Melton GB. Using language models to identify relevant new information in inpatient clinical notes. AMIA Annu Symp Proc. 2014 Nov 14;2014:1268-76. eCollection 2014. PubMed PMID: 25954438; PubMed Central PMCID: PMC4419897.
35. Zhang R, Pakhomov SVS, Arsoniadis EG, Lee JT, Wang Y, Melton GB. Detecting clinically relevant new information in clinical notes across specialties and settings. BMC Med Inform Decis Mak. 2017;17(Suppl 2):68. Published 2017 Jul 5. doi:10.1186/s12911-017-0464-y. PubMed PMID: 28699564. PubMedCentral PMCID: PMC5506580.
36. Zhang R, Pakhomov S, Melton GB. Longitudinal analysis of new information types in clinical notes. AMIA Jt Summits Transl Sci Proc. 2014 Apr 7;2014:232-7. eCollection 2014. PubMed PMID: 25717418; PubMed Central PMCID: PMC4333708.

References

1. Committee WaM. Title IV - Health Information Technology for Economic and Clinical Health Act. 2009 [cited 2011 June 20]; Available from: http://waysandmeans.house.gov/media/pdf/110/hit2.pdf.
2. Bates DW, Gawande AA. Improving safety with information technology. N Engl J Med. 2003 Jun 19;348(25):2526-34.
3. Karsh BT, Weinger MB, Abbott PA, Wears RL. Health information technology: fallacies and sober realities. J Am Med Inform Assoc. 2010 Nov-Dec;17(6):617-23.
4. Patel VL, Kaufman DR, Arocha JF. Emerging paradigms of cognition in medical decision-making. J Biomed Inform. 2002 Feb;35(1):52-75.
5. Rosenbloom ST, Denny JC, Xu H, Lorenzi N, Stead WW, Johnson KB. Data from clinical notes: a perspective on the tension between structure and flexible documentation. J Am Med Inform Assoc. 2011 Mar-Apr;18(2):181-6.
6. Coiera E. When conversation is better than computation. J Am Med Inform Assoc. 2000 May-Jun;7(3):277-86.
7. Starren J, Johnson SB. An object-oriented taxonomy of medical data presentations. J Am Med Inform Assoc. 2000 Jan-Feb;7(1):1-20.
8. Payne TH, tenBroek AE, Fletcher GS, Labuguen MC. Transition from paper to electronic inpatient physician notes. J Am Med Inform Assoc. 2010 Jan-Feb;17(1):108-11.
9. Wrenn JO, Stein DM, Bakken S, Stetson PD. Quantifying clinical narrative redundancy in an electronic health record. J Am Med Inform Assoc. 2010 Jan- Feb;17(1):49-53.
10. Chandler P, Sweller J. Cognitive Load Theory and the Format of Instruction. Cognition and Instruction. 1991;8(4):293-332.
11. Simon HA, Chase WG. Skill in chess. American Scientist. 1973;61(4):394-403. 12. Sweller J. Cognitive load during problem-solving: effects on learning. Cognitive Science. 1988;12(2):257-85.
12. Sweller J. Cognitive load during problem-solving: effects on learning. Cognitive Science. 1988;12(2):257-85.
13. Braddock CH, 3rd, Snyder L. The doctor will see you shortly. The ethical significance of time for the patient-physician relationship. J Gen Intern Med. 2005 Nov;20(11):1057-62.
14. Dugdale DC, Epstein R, Pantilat SZ. Time and the patient-physician relationship. J Gen Intern Med. 1999 Jan;14 Suppl 1:S34-40.
15. Van Vleck TT, Stein DM, Stetson PD, Johnson SB. Assessing data relevance for automated generation of a clinical summary. AMIA Annu Symp Proc. 2007:761-5.
16. Nguyen VD, Almoosa KF, Patel B, Patel VL. Electronic Health Records: Friend or Foe to the Decision Making Process in the Intensive Care Unit. AMIA Annu Symp Proc.2010:1194.
17. Weir CR, Nebeker JR. Critical issues in an electronic documentation system. AMIA Annu Symp Proc. 2007:786-90.
18. Cao H, Markatou M, Melton GB, Chiang MF, Hripcsak G. Mining a clinical data warehouse to discover disease-finding associations using co-occurrence statistics. AMIA Annu Symp Proc. 2005:106-10.
19. Weed LL. Medical records that guide and teach. N Engl J Med. 1968 Mar 14;278(11):593-600.
20. Weed LL. Medical records that guide and teach. N Engl J Med. 1968 Mar 21;278(12):652-7 concl.
21. Pakhomov S, Weston SA, Jacobsen SJ, Chute CG, Meverden R, Roger VL. Electronic medical records for clinical research: application to the identification of heart failure. Am J Manag Care. 2007 Jun;13(6 Part 1):281-8.

22. Hersh WR. Adding value to the electronic health record through secondary use of data for quality assurance, research, and surveillance. Am J Manag Care. 2007 Jun;13(6 Part 1):277-8.
23. McCray AT, Srinivasan S, Browne AC. Lexical methods for managing variation in biomedical terminologies. Proc Annu Symp Comput Appl Med Care. 1994:235-9.
24. Cohen KB, Palmer M, Hunter L. Nominalization and alternations in biomedical language. PLoS One. 2008;3(9):e3158.
25. Hultman G, Zhang R, Knoll B, McEwan R, Skube S, Melton GB. Visualization of Clinically Relevant New Information from Clinical Reports in the EHR. AMIA Jt Summits Transl Sci Proc. 2018. (In Press).
26. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of NLP-PIER: A Clinical Document Search Engine for Researchers. Stud Health Technol Inform. 2017;245:1269. PubMed PMID: 29295354; PubMed Central PMCID: PMC6188640.
27. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of an Unstructured Clinical Document Query Tool for Researchers. Proceedings of the American Medical Informatics Association Informatics Summit Symposium. 2018:84-93.
28. Rizvi RF, Harder KA, Hultman GM, Adam TJ, Kim M, Pakhomov SV, Melton GB. A comparative observational study of inpatient clinical note-entry and reading/retrieval styles adopted by physicians. Int J Med Inform. 2016 Jun;90:1-11. doi: 10.1016/j.ijmedinf.2016.02.011. Epub 2016 Mar 2. PubMed PMID: 27103191; PubMed Central PMCID: PMC5534410.
29. http://www.qsrinternational.com/product. Accessed December 19, 2018.
30. Rizvi RF, Marquard JL, Seywerd MA, Adam TJ, Elison JT, Hultman GM, Harder KA, Melton GB. Usability Evaluation of an EHR's Clinical Notes Interface from Attendings and Residents Perspectives-An Exploratory Study. Studies in Health Technology and Informatics (MedInfo 2017). 2017;245:1128-1132. PMID: 29295278.
31. Hultman G, Arsoniadis E, Marquard J, Rizvi R, Khairat S, Fickau K, Melton GB. Usability Testing of an Ambulatory Navigator. Proceedings of the American Medical Informatics Annual Symposium. November 14-18, 2015. San Francisco, CA.
32. Hultman G, Marquard J, Arsoniadis E, Mink PJ, Rizvi R, Ramer T, Khairat S, Fickau K, Melton GB. Usability Testing of Two Ambulatory EHR Navigators. Applied Clinical Informatics. 2016 Jun 15;7(2):502-15. doi: 10.4338/ACI-2015-10-RA-0129. eCollection 2016. PMID: 27437057 PMCID: PMC4941856.
33. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of an Unstructured Clinical Document Query Tool for Researchers. Proceedings of the American Medical Informatics Association Informatics Summit Symposium. 2018:84-93.
34. Hultman G, McEwan R, Pakhomov S, Lindemann E, Skube S, Melton GB. Usability Evaluation of NLP-PIER: A Clinical Document Search Engine for Researchers. Stud Health Technol Inform. 2017;245:1269. PubMed PMID: 29295354; PubMed Central PMCID: PMC6188640.
35. Hultman G, McEwan R, Pakhomov S, Skube S, Melton GB. Usability Testing of a Clinical Document Search Engine for Researchers. AMIA Jt Summits Transl Sci Proc. March 27-30, 2017. San Francisco, CA.
36. https://www.nlm.nih.gov/research/umls. Accessed December 19, 2018.
37. http://www.globaldelight.com/voila.html. Accessed December 19, 2018.
38. Brooke J. SUS-A quick and dirty usability scale. Usability Eval Ind. 1996;189(194):4–7.

39. Hart SG. NASA-task load index (NASA-TLX); 20 years later. In: Proceedings of the human factors and ergonomics society annual meeting; Sage Publications. 2006. pp. 904–8.
40. Zhang R, Pakhomov SV, Lee JT, Melton GB. Using language models to identify relevant new information in inpatient clinical notes. AMIA Annu Symp Proc. 2014 Nov 14;2014:1268-76. eCollection 2014. PubMed PMID: 25954438; PubMed Central PMCID: PMC4419897.
41. Zhang R, Pakhomov S, Melton GB. Longitudinal analysis of new information types in clinical notes. AMIA Jt Summits Transl Sci Proc. 2014 Apr 7;2014:232-7. eCollection 2014. PubMed PMID: 25717418; PubMed Central PMCID: PMC4333708.
42. Zhang R, Pakhomov SV, Lee JT, Melton GB. Using language models to identify relevant new information in inpatient clinical notes. AMIA Annu Symp Proc. 2014 Nov 14;2014:1268-76. eCollection 2014. PubMed PMID: 25954438; PubMed Central PMCID: PMC4419897.
43. Zhang R, Pakhomov S, Melton GB. Longitudinal analysis of new information types in clinical notes. AMIA Jt Summits Transl Sci Proc. 2014 Apr 7;2014:232-7. eCollection 2014. PubMed PMID: 25717418; PubMed Central PMCID: PMC4333708.
44. Zhang R, Pakhomov SVS, Arsoniadis EG, Lee JT, Wang Y, Melton GB. Detecting clinically relevant new information in clinical notes across specialties and settings. BMC Med Inform Decis Mak. 2017;17(Suppl 2):68. Published 2017 Jul 5. doi:10.1186/s12911-017-0464-y.
45. Zhang R, Adam TJ, Simon G, Cairelli MJ, Rindflesch T, Pakhomov S, Melton GB. Mining Biomedical Literature to Explore Interactions between Cancer Drugs and Dietary Supplements. AMIA Jt Summits Transl Sci Proc. 2015 Mar 23;2015:69-73. eCollection 2015. PubMed PMID: 26306241; PubMed Central PMCID: PMC4525230.
46. Zhang R, Manohar N, Arsoniadis E, Wang Y, Adam TJ, Pakhomov SV, Melton GB. Evaluating Term Coverage of Herbal and Dietary Supplements in Electronic Health Records. AMIA Annu Symp Proc. 2015 Nov 5;2015:1361-70. eCollection 2015. PubMed PMID: 26958277; PubMed Central PMCID: PMC4765597.
47. Zhang R, Cairelli MJ, Fiszman M, Rosemblat G, Kilicoglu H, Rindflesch TC, Pakhomov SV, Melton GB. Using semantic predications to uncover drug-drug interactions in clinical data. J Biomed Inform. 2014 Jun;49:134-47. doi: 10.1016/j.jbi.2014.01.004. Epub 2014 Jan 19. PubMed PMID: 24448204; PubMed Central PMCID: PMC4058371.
48. Sun D, Sarda G, Skube SJ, Blaes AH, Khairat S, Melton GB, Zhang R. Phenotyping and Visualizing Infusion-Related Reactions for Breast Cancer Patients. Stud Health Technol Inform. 2017;245:599-603. PubMed PMID: 29295166; PubMed Central PMCID: PMC5760174.
49. Sun D, Simon GJ, Skube S, Blaes AH, Melton GB, Zhang R. Causal Phenotyping for Susceptibility to Cardiotoxicity from Antineoplastic Breast Cancer Medications. AMIA Annu Symp Proc. 2018 Apr 16;2017:1655-1664. eCollection 2017. PubMed PMID: 29854236; PubMed Central PMCID: PMC5977581.
50. Hultman G, Marquard J, Kandaswamy S, Lindemann EA, Melton GB. How do physicians read electronic progress notes? Proceedings of the American Medical Informatics Association Symposium. November 4-8, 2017. Washington, DC.
51. Hultman GM, Marquard J, Ighile O, Farri O, Lindemann E, Arsoniadis EG, Pakhomov SVS, Melton GB. Does Section Order Affect Physicians' Experiences Reviewing Ambulatory Progress Notes? Proceedings of the American Medical Informatics Annual Symposium. November 12-16, 2016. Chicago, IL.
52. Hultman GM, Marquard J, Swaminathan K, Lindemann EA, Pakhomov S, Melton GB. Electronic Progress Note Reading Patterns: An Eye Tracking Analysis. Stud Health Technol Inform. 2019. *(Submitted).*

53. McEwan R, Melton GB, Knoll BC, Wang Y, Hultman G, Dale JL, Meyer T, Pakhomov SV. NLP-PIER: A Scalable Natural Language Processing, Indexing, and Searching Architecture for Clinical Notes. AMIA Jt Summits Transl Sci Proc. 2016 Jul 20;2016:150-9. eCollection 2016. PubMed PMID: 27570663; PubMed Central PMCID: PMC5001745.